

```
In [1]: import pandas as pd

train = pd.read_csv("train.csv")

train.head()
```

```
Out[1]:
```

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	Loan_Amount_Term	Credit_History	Property_Area	Loan_Status
0	LP001002	Male	No	0	Graduate	No	5849	1168	360	1	area	A
1	LP001003	Male	Yes	1	Graduate	No	4583	2608	360	1	area	A
2	LP001005	Male	Yes	0	Graduate	Yes	3000	1312	360	1	area	A
3	LP001006	Male	Yes	0	Not Graduate	No	2583	966	360	1	area	A
4	LP001008	Male	No	0	Graduate	No	6000	1968	360	1	area	A

```
In [2]: train.shape
```

```
Out[2]: (614, 13)
```

```
In [5]: train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 13 columns):
#   Column                Non-Null Count  Dtype
---  -
0   Loan_ID               614 non-null    object
1   Gender                601 non-null    object
2   Married               611 non-null    object
3   Dependents            599 non-null    object
4   Education             614 non-null    object
5   Self_Employed         582 non-null    object
6   ApplicantIncome       614 non-null    int64
7   CoapplicantIncome     614 non-null    float64
8   LoanAmount            592 non-null    float64
9   Loan_Amount_Term      600 non-null    float64
10  Credit_History         564 non-null    float64
11  Property_Area          614 non-null    object
12  Loan_Status            614 non-null    object
dtypes: float64(4), int64(1), object(8)
memory usage: 62.5+ KB
```

```
In [7]: # checking for missing values
```

```
train.isna().sum()
```

```
Out[7]: Loan_ID      0
Gender      13
Married     3
Dependents  15
Education   0
Self_Employed 32
ApplicantIncome 0
CoapplicantIncome 0
LoanAmount  22
Loan_Amount_Term 14
Credit_History 50
Property_Area 0
Loan_Status 0
dtype: int64
```

```
In [9]: train.describe()
```

```
Out[9]:
```

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	614.000000	614.000000	592.000000	600.000000	564.000000
mean	5403.459283	1621.245798	146.412162	342.000000	0.842184
std	6109.041673	2926.248369	85.587325	65.120411	0.364814
min	150.000000	0.000000	9.000000	12.000000	0.000000
25%	2877.500000	0.000000	100.000000	360.000000	1.000000
50%	3812.500000	1188.500000	128.000000	360.000000	1.000000
75%	5795.000000	2297.250000	168.000000	360.000000	1.000000
max	81000.000000	41667.000000	700.000000	480.000000	1.000000

```
In [11]: train.describe(include=[object])
```

```
Out[11]:
```

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	Property_Area
count	614	601	611	599	614	582	614
unique	614	2	2	4	2	2	3
top	LP001002	Male	Yes	0	Graduate	No	Semiurban
freq	1	489	398	345	480	500	233

```
In [13]: # dropping PassengerId, Name and Ticket
```

```
train = train.drop(['Loan_ID'], axis=1)
```

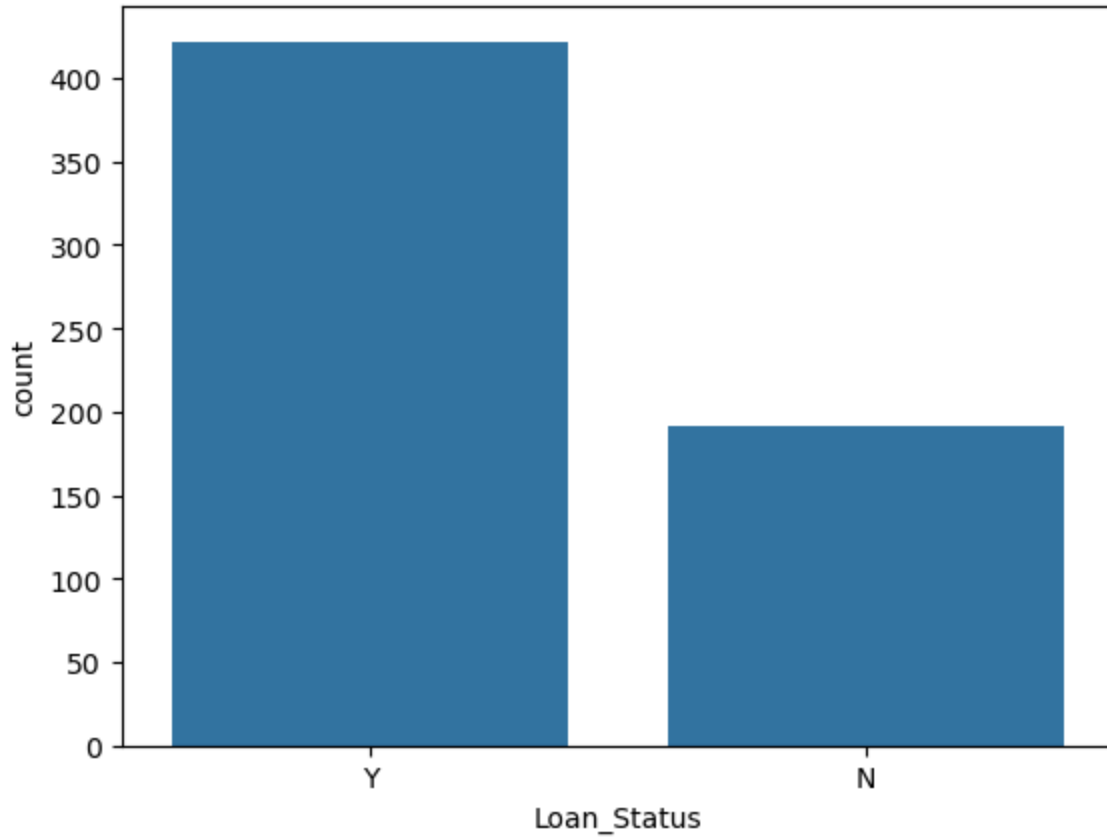
```
In [15]: train['Loan_Status'].value_counts()
```

```
Out[15]: Loan_Status
Y      422
N      192
Name: count, dtype: int64
```

```
In [17]: import seaborn as sns

sns.countplot(x=train['Loan_Status'])
```

```
Out[17]: <Axes: xlabel='Loan_Status', ylabel='count'>
```

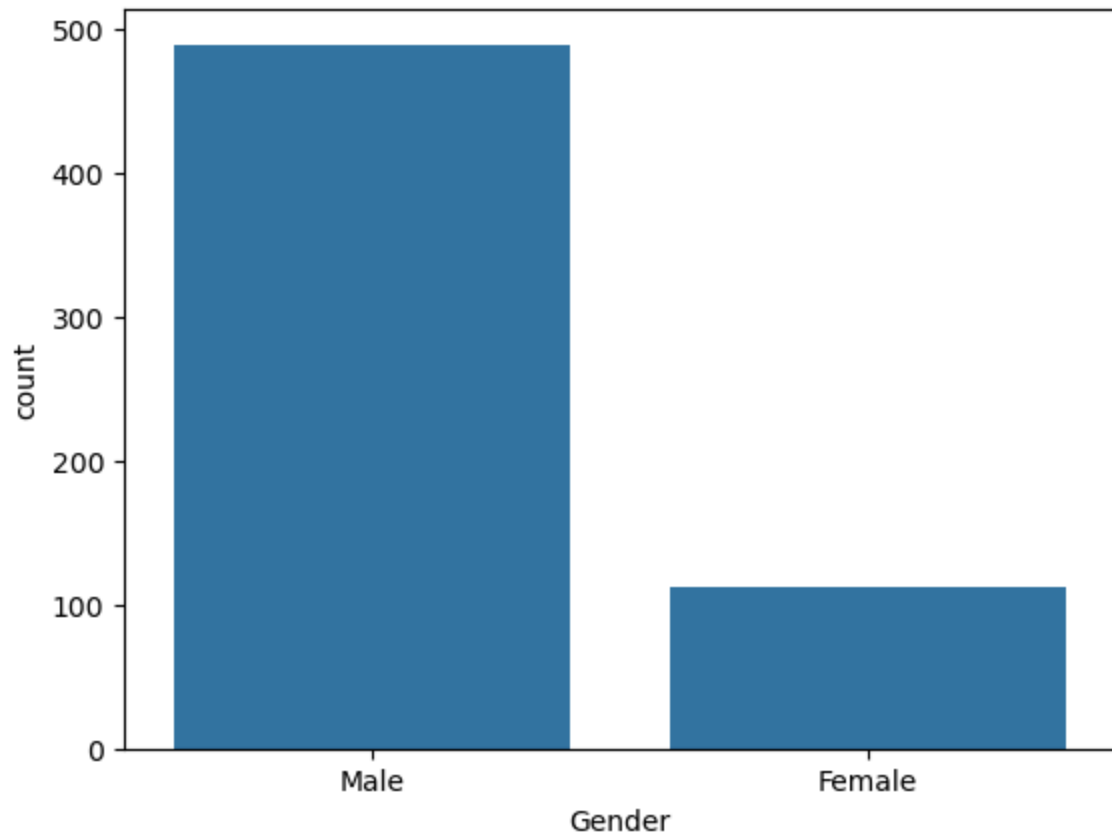


```
In [19]: train['Gender'].value_counts()
```

```
Out[19]: Gender
Male      489
Female    112
Name: count, dtype: int64
```

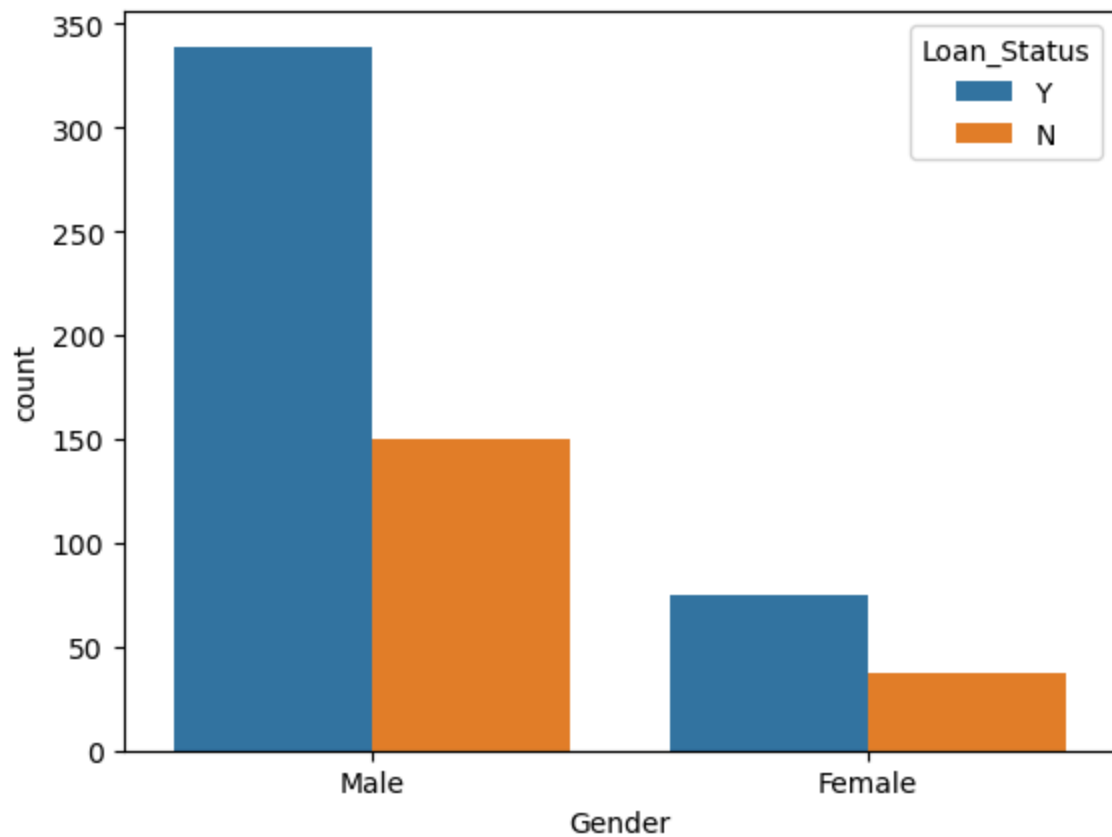
```
In [21]: sns.countplot(x=train['Gender'])
```

```
Out[21]: <Axes: xlabel='Gender', ylabel='count'>
```



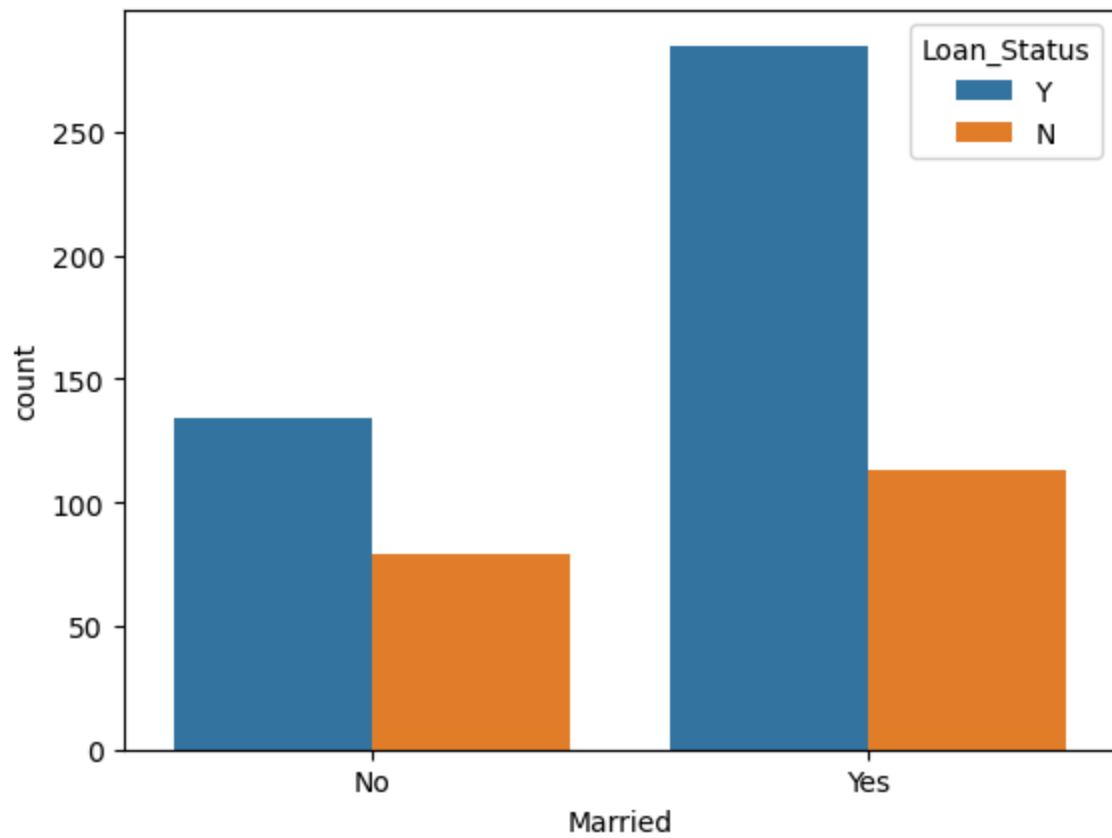
```
In [23]: sns.countplot(x=train['Gender'], hue=train['Loan_Status'])
```

```
Out[23]: <Axes: xlabel='Gender', ylabel='count'>
```



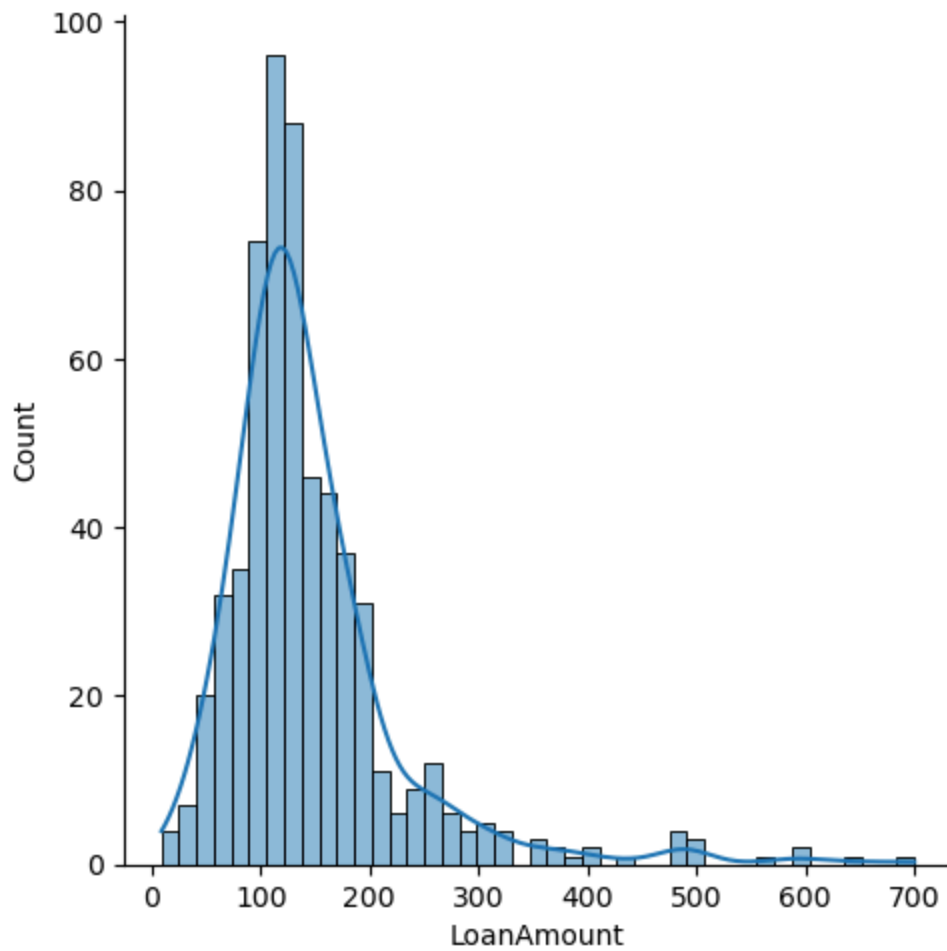
```
In [25]: sns.countplot(x='Married', data=train, hue='Loan_Status')
```

```
Out[25]: <Axes: xlabel='Married', ylabel='count'>
```



```
In [27]: sns.displot(train['LoanAmount'], kde=True)
```

```
Out[27]: <seaborn.axisgrid.FacetGrid at 0x2477fad2f00>
```



```
In [29]: train['LoanAmount'].skew()
```

```
Out[29]: 2.677551679256059
```

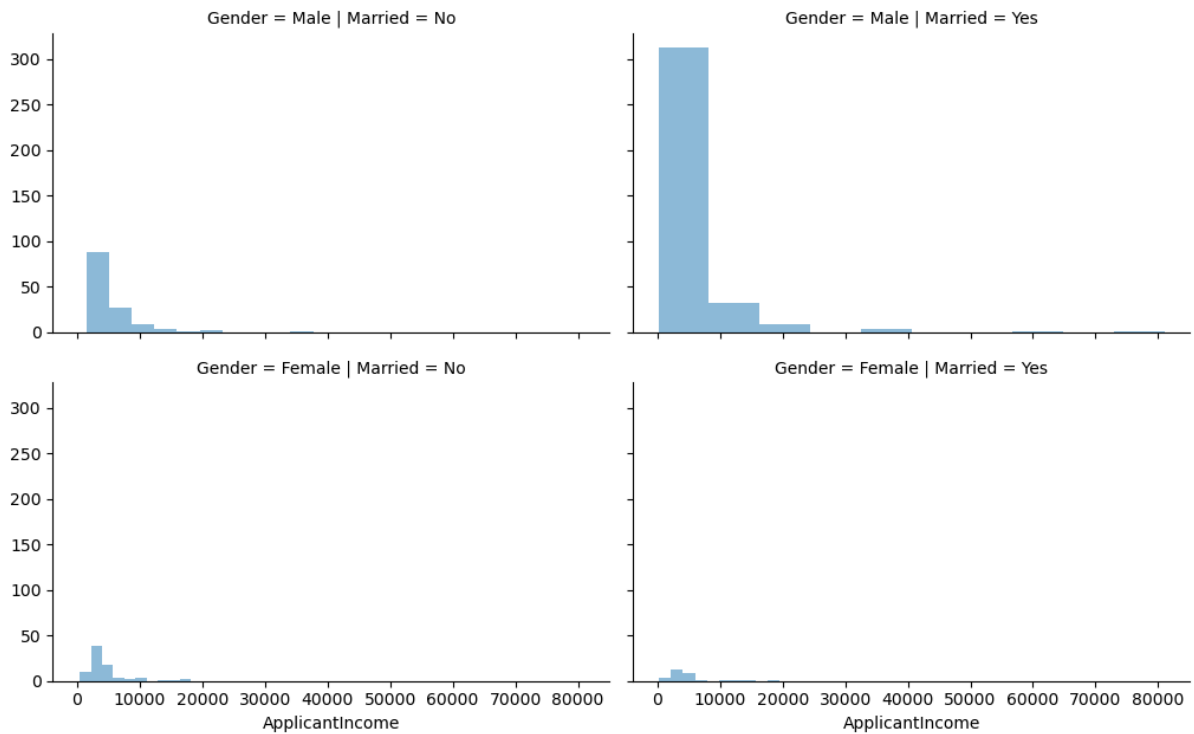
```
In [31]: import matplotlib.pyplot as plt

grid = sns.FacetGrid(train, row='Gender', col='Married', height=3.2, aspect=1.6)

grid.map(plt.hist, 'ApplicantIncome', alpha=.5, bins=10)

grid.add_legend()
```

```
Out[31]: <seaborn.axisgrid.FacetGrid at 0x2477faa8b60>
```



```
In [33]: rplot(train, hue='Loan_Status', height=2.5)
```

```
-----
NameError                                Traceback (most recent call last)
Cell In[33], line 1
----> 1 rplot(train, hue='Loan_Status', height=2.5)

NameError: name 'rplot' is not defined
```

```
In [35]: train.isna().sum()
```

```
Out[35]: Gender          13
Married              3
Dependents          15
Education            0
Self_Employed       32
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           22
Loan_Amount_Term     14
Credit_History      50
Property_Area        0
Loan_Status          0
dtype: int64
```

```
In [43]: train['Gender'] = train['Gender'].fillna(train['Gender'].mode()[0])
```

```
In [45]: train['Married'] = train['Married'].fillna(train['Married'].mode()[0])
```

```
In [41]: train['Dependents'].fillna(train['Dependents'].mode()[0], inplace=True)
```

C:\Users\Vaish\AppData\Local\Temp\ipykernel_24124\869824710.py:1: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.

```
train['Dependents'].fillna(train['Dependents'].mode()[0], inplace=True)
```

In [47]: `train['Self_Employed'].fillna(train['Self_Employed'].mode()[0], inplace=True)`

C:\Users\Vaish\AppData\Local\Temp\ipykernel_24124\1340705068.py:1: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.

The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.

```
train['Self_Employed'].fillna(train['Self_Employed'].mode()[0], inplace=True)
```

In [49]: `train['LoanAmount'].fillna(train['LoanAmount'].median(), inplace=True)`

C:\Users\Vaish\AppData\Local\Temp\ipykernel_24124\3228316714.py:1: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.

The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.

```
train['LoanAmount'].fillna(train['LoanAmount'].median(), inplace=True)
```

In [51]: `train['Loan_Amount_Term'].fillna(train['Loan_Amount_Term'].mode()[0], inplace=True)`

C:\Users\Vaish\AppData\Local\Temp\ipykernel_24124\2271678739.py:1: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.

```
train['Loan_Amount_Term'].fillna(train['Loan_Amount_Term'].mode()[0], inplace=True)
```

```
In [53]: train['Credit_History'].skew()
```

```
Out[53]: -1.8823610612186696
```

```
In [55]: train.isna().sum()
```

```
Out[55]: Gender                0
Married                0
Dependents             0
Education              0
Self_Employed          0
ApplicantIncome        0
CoapplicantIncome      0
LoanAmount             0
Loan_Amount_Term       0
Credit_History        50
Property_Area          0
Loan_Status            0
dtype: int64
```

```
In [57]: from sklearn.preprocessing import LabelEncoder

feature_col = ['Gender', 'Married', 'Dependents', 'Education', 'Self_Employed', 'Property_Area']

le = LabelEncoder()

for col in feature_col:

    train[col] = le.fit_transform(train[col])
```

```
In [59]: train.Loan_Status = train.Loan_Status.replace({"Y": 1, "N": 0})
```

C:\Users\Vaish\AppData\Local\Temp\ipykernel_24124\1785350424.py:1: FutureWarning: Downcasting behavior in `replace` is deprecated and will be removed in a future version. To retain the old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`

```
train.Loan_Status = train.Loan_Status.replace({"Y": 1, "N": 0})
```

```
In [61]: train.head(3)
```

```
Out[61]:
```

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coapplicant
0	1	0	0	0	0	5849	
1	1	1	1	0	0	4583	
2	1	1	0	0	1	3000	

```
In [64]: train['total_income'] = train['ApplicantIncome'] + train['CoapplicantIncome']
```

```
In [66]: train.drop(columns=['ApplicantIncome', 'CoapplicantIncome'], inplace=True)
```

```
In [68]: train.head(3)
```

```
Out[68]:
```

	Gender	Married	Dependents	Education	Self_Employed	LoanAmount	Loan_Amount_T
0	1	0	0	0	0	128.0	30
1	1	1	1	0	0	128.0	30
2	1	1	0	0	1	66.0	30

```
In [70]: train.columns
```

```
Out[70]: Index(['Gender', 'Married', 'Dependents', 'Education', 'Self_Employed',
               'LoanAmount', 'Loan_Amount_Term', 'Credit_History', 'Property_Area',
               'Loan_Status', 'total_income'],
              dtype='object')
```

```
In [72]: rel_feat = ['Gender', 'Married', 'Dependents', 'Education', 'Self_Employed',
                    'LoanAmount', 'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'to
```

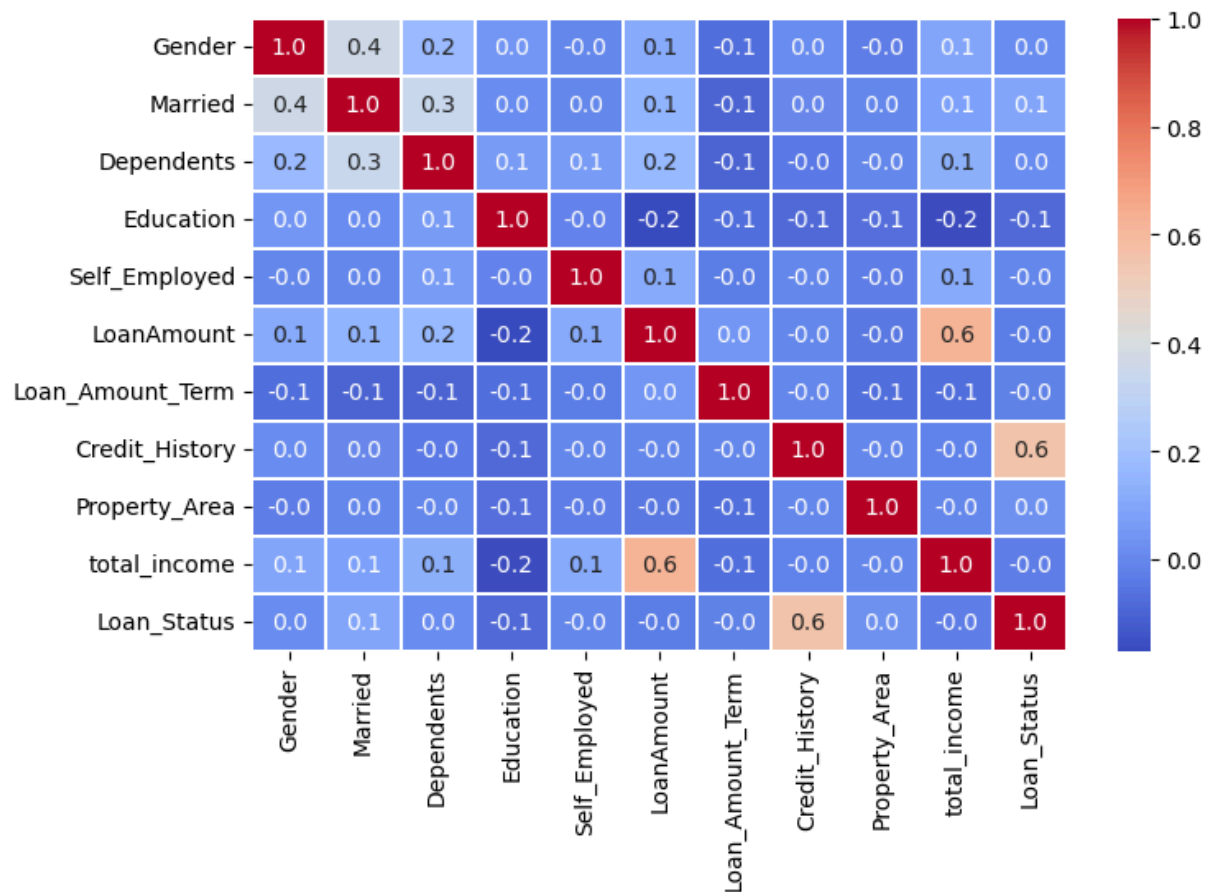
```
In [74]: rel_feat_corr = train.corr()['Loan_Status'][['Gender', 'Married', 'Dependents', 'Ed
                    'Self_Employed', 'LoanAmount', 'Loan_A
                    'Credit_History', 'Property_Area', 'to
```

```
In [76]: rel_feat_corr
```

```
Out[76]: Gender          0.017987
Married          0.091478
Dependents       0.010118
Education       -0.085884
Self_Employed   -0.003700
LoanAmount      -0.033214
Loan_Amount_Term -0.022549
Credit_History   0.561678
Property_Area    0.032112
total_income    -0.031271
Name: Loan_Status, dtype: float64
```

```
In [78]: plt.figure(figsize=(8,5))

sns.heatmap(train[rel_feat].corr(), cmap='coolwarm', annot=True, fmt='.1f', linewidth
plt.show()
```



```
In [80]: #Separating target variable and other variables
```

```
X=train.drop(columns='Loan_Status')
```

```
y=train['Loan_Status']
```

```
In [82]: #Splitting the data into train and test sets
```

```
from sklearn.model_selection import train_test_split
```

```
X_train,X_test,y_train,y_test=train_test_split(X, y, test_size=0.30, random_state=7
```

```
In [84]: from sklearn.ensemble import RandomForestClassifier
```

```
rf = RandomForestClassifier(n_estimators=100, max_features='sqrt')
```

```
rf = rf.fit(X_train, y_train)
```

```
rf_pred=rf.predict(X_test).astype(int)
```

```
In [86]: from sklearn.metrics import confusion_matrix, classification_report, accuracy_score

print(confusion_matrix(y_test, rf_pred))

print(classification_report(y_test, rf_pred))

print("Accuracy:", accuracy_score(y_test, rf_pred))
```

```
[[ 31  30]
 [  9 115]]
```

	precision	recall	f1-score	support
0	0.78	0.51	0.61	61
1	0.79	0.93	0.86	124
accuracy			0.79	185
macro avg	0.78	0.72	0.73	185
weighted avg	0.79	0.79	0.78	185

Accuracy: 0.7891891891891892

```
In [ ]:
```